Feature Hashing

NYU Large Scale Learning Class

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Hand crafted features, built up iteratively over time, each new feature fixing a discovered problem. In essence, boosting where humans function as the weak learner.

1. +Good understanding of what’s happening.
2. +Never fail to learn the obvious.
3. +Small RAM usage.
4. -Slow at test time. Intuitive features for humans can be hard
5. -Low Capacity. A poor fit for large datasets. (Boosted)
   Decision trees are a good compensation on smaller datasets.
6. -High persontime.
Features in Practice: Learned Features

Use a nonlinear/nonconvex possibly deep learning algorithm.

1. **+Good results** in Speech & Vision.
2. **+Fast** at test time.
3. **+High capacity.** Useful on large datasets.
4. **-Slow training.** Days to weeks are common.
5. **-Wizardry may be required.**
An example: for each (word, ad) pair keep track of empirical expectation of click $\hat{E}[c|\text{(word, ad)}]$. 

1. +High capacity.
2. +Fast learning. Counting is easy on map-reduce architectures.
3. +Fast test time. Lookup some numbers, then compute an easy prediction.
4. -High RAM usage. Irrelevant features take RAM.
5. -Correlation effects lost. Adding explicit conjunction features takes even more RAM.
Generate a feature for every word, ngram, skipgram, pair of (ad word, query word), etc... and use high dimensional representation.

1. +High capacity.
2. +Correlation effects nailed.
3. +fast test time. Lookup some numbers, then compute an easy prediction.
4. -Slow learning Linear faster than decision tree, but parallel is tricky.
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Features in Practice: sparse words

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word, query word), etc... and use high dimensional representation.

1. +High capacity.

2. +Correlation effects nailed.

3. +fast test time. Lookup some numbers, then compute an easy prediction. This lecture.

4. -Slow learning Linear faster than decision tree, but parallel is tricky. This lecture + Allreduce lecture.

5. -High RAM usage This lecture.
What is hashing?

**Hash function**: string $\rightarrow \{0, 1\}^b$

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**Hash table** = Hash function + Array$\langle$ Pair$\langle$string, int$\rangle$ $\rangle$ of length $\{0, 1\}^b$

**Perfect hash** = overfit decision tree mapping $n$ fixed (and known in advance) strings to integers $\{1, n\}$. 
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More weights is better!
Objection: Collisions!

Valid sometimes: particularly with low dimensional hand engineered features.
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Theorem: If a feature is duplicated $O(\log n)$ times when there are $O(n)$ features, at least one version of the feature is uncollided when hashing with $\log(n \log n)$ bits.
Proof: Similar to Bloom filter proof.
Example 1: CCAT RCV1

1 | tuesday year million short compan vehicl line stat financ commit
exchang plan corp subsid credit issu debt pay gold bureau prelimin
refin billion telephon time draw
-1 | econom stock rate month year invest week produc report
govern pric index million shar end reserv foreign research inflat gdp
growth export consum output annual industr cent exchang project
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Run:
vw -b 24 --loss_function logistic --ngram 2 --skips 4 -c rcv1.train.raw.txt --binary
to see progressive validation loss 4.5%: about 0.6% better than linear on base features.
Objection: Incomprehensible!
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Use `--audit` to decode. Or, keep your own dictionary on the side if desirable.
`vw-varinfo rcv1.test.raw.txt.gz` = perl script in VW distribution for automatically decoding and inspecting results.
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-q df pairs every feature in namespaces beginning with d with every feature in namespaces beginning with f.

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But how?

Feature = (index, weight)
pair_weight = d_weight * f_weight
pair_index = (d_index * magic + f_index) & mask
This is done inline for speed.
Use of Hash: Ngrams

2gram = a feature for every pair of adjacent words.
3gram = a feature for every triple of adjacent words, etc...
ngram = ...

Features computed in the same fashion as for -q

(More clever solution = rolling hash, not yet implemented.)

Computed by the parser on the fly (since #features/example only grows linearly).
In many applications, you must have multiple predictors. Hashing allows all these to be mapped into the same array using a different offsets saving gobs of RAM and programming headaches.

–oaa, –ect, –csoaa, and others.
Example 2: Mass Personalized Spam Filtering

1. $3.2 \times 10^6$ labeled emails.
2. 433167 users.
3. $\sim 40 \times 10^6$ unique tokens.

How do we construct a spam filter which is personalized, yet uses global information?
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Bad answer: Construct a global filter + 433167 personalized filters using a conventional hashmap to specify features. This might require $433167 \times 40 \times 10^6 \times 4 \sim 70$ Terabytes of RAM.
Use hashing to predict according to: \( \langle w, \phi(x) \rangle + \langle w, \phi_u(x) \rangle \)

- **X**: \( \text{NEU} \), \( \text{Votre} \), \( \text{Apotheke en ligne} \), \( \text{Euro} \), ...
- **X_l**: \( \text{USER123_NEU} \), \( \text{USER123_Votre} \), \( \text{USER123_Apotheke} \), \( \text{USER123_en ligne} \), \( \text{USER123_Euro} \), ...
- **X_h**: 
  - 323:
    - 0: 5235
    - 0: 0
    - 123: 0
    - 626: 232
    - ...

(in VW: specify the userid as a feature and use -q)
Results

\[2^{26}\] parameters = 64M parameters = 256MB of RAM. An \textit{x270K} savings in RAM requirements.
Features sometimes collide, which is scary, but then you love it.

Generate a feature for every word, ngram, skipgram, pair of (ad word, query word), etc... and use high dimensional representation.

1. +High capacity.
2. +Correlation effects nailed.
4. +Fast Learning (with Online + parallel techniques. See talks.)
5. +/-Variable RAM usage. Highly problem dependent but fully controlled.

Another cool observation: Online learning + Hashing = learning algorithm with fully controlled memory footprint ⇒ Robustness.
References, prequels


3. Apparently used by others as well, internally.

4. Many use hashtables which store the original item or a 64+ bit hash of the original item.
2007, Langford, Li, Strehl, Vowpal Wabbit released.

2008, Ganchev & Dredze, ACL workshop: A hash function is as good as a hashmap empirically.

2008/2009, VW Reimplementation/Reimagination/Integration in Stream (James Patterson & Alex Smola) and Torch (Jason Weston, Olivier Chapelle, Kilian).

2009, AIStat Qinfeng Shi et al, Hash kernel definition, Asymptopia Redundancy analysis